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Digital health competence among healthcare professionals: A cross-sectional cluster analysis across 19 countries and regions

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A R T I C L E I N F O

Keywords:
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A B S T R A C T

Background: The worldwide acceleration of digital transformation in healthcare underscores the need for professionals to continuously adapt and sustain robust digital health competence, shaped not only by individual characteristics and institutional environments but also by broader social, cultural, and geopolitical factors.
Objective: This study aimed to identify distinct clusters of digital health competence among healthcare professionals across 19 diverse countries and regions, and to examine the factors influencing the development and distribution of these competence clusters.
Methods: A cross-sectional international survey study was conducted between 2023 and 2024, using a validated survey instrument measuring digital health competence and its influencing factors. Data were collected from healthcare professionals in 19 countries and regions (n = 6440; n = 5945 used for this study), following a harmonised protocol with shared demographic templates and instruments. K-means cluster analysis was employed to derive digital competence profiles, with comparative analyses conducted to investigate associations between the identified clusters and individual characteristics (e.g., age, education, professional experience).
Results: Five distinct clusters of digital health competence were identified: (1) Beginners, (2) Developing Professionals, (3) Emerging Users, (4) Proficient Practitioners, and (5) Pioneers. Higher competence clusters (4 and 5) were associated with younger age, higher education, hospital-based work, and stronger perceived support from management, organisational structures, and colleagues. In contrast, lower-performing clusters reported limited digital engagement and minimal support. Perceived leadership influence, particularly managerial commitment to digital change, was a key differentiator across clusters.
Conclusions: The findings demonstrate substantial variation in digital health competence across healthcare professionals internationally. Cluster-specific strategies, such as targeted upskilling, peer mentoring, and leadership engagement, are needed to address competence gaps. The results provide a foundation for policy development and workforce training frameworks aimed at strengthening digital readiness in global healthcare systems. Future research should explore longitudinal competence development and evaluate targeted interventions.

What is already known

- Digital transformation in healthcare requires professionals to continuously adapt their digital competences.
- Individual, organisational, and cultural factors influence the development of digital health competence.
- International variations exist in the digital readiness of healthcare professionals.

What this paper adds

- Identifies five empirically distinct digital health competence profiles among healthcare professionals across 19 countries, ranging from beginners to pioneers, with large and meaningful between-cluster differences in digital health competence.
- Shows that higher digital health competence is consistently associated with stronger perceived organisational, managerial, and collegial support, highlighting leadership and workplace context as key determinants of competence development.
- Demonstrates that digital health competence is uneven across competence domains, with counselling, ethical use, and evaluation of digital solutions emerging as persistent gaps even among otherwise digitally proficient professionals.

1. Introduction

The rapid digital transformation in healthcare is reshaping how health services are delivered, managed, and experienced worldwide (World Health Organisation (WHO), 2021; Organisation for Economic Co-operation and Development (OECD), 2019). Healthcare systems globally are undergoing profound changes, driven by technological innovations such as telemedicine, electronic health records, artificial intelligence (AI), internet-of-things, and wearable devices. These transformations aim to enhance care quality, patient safety, and operational efficiency (Amees, 2023; Longhini et al., 2022; WHO, 2020). Central to successfully navigating this digital shift are the competences of healthcare professionals, whose ability to effectively utilise digital health solutions directly impacts clinical outcomes, patient satisfaction, and overall system performance (OECD, 2020; Laukka et al., 2020). Recognising the pivotal role of digital health competences, major global health organisations, including the World Health Organisation (WHO, 2021) and the Organisation for Economic Co-operation and Development (OECD, 2020), have emphasised the critical need for comprehensive digital literacy among healthcare workforces to ensure equitable, accessible, and high-quality healthcare services in increasingly digital environments.

In addition to the increasing emphasis on digital competences at the individual level, recent global research has underscored the importance of understanding these competences within the broader system-wide digital determinants of health. The WHO-led global scoping review and expert consensus by van Kessel et al. (2025) identify digital access, infrastructure, governance, organisational readiness, and workforce capability as interconnected determinants that shape whether digital health solutions can be adopted effectively across health systems. Positioning healthcare professionals' digital competence within this digital determinants of health framework highlights that competence gaps are not solely individual challenges but are deeply shaped by organisational, cultural, and policy environments. This perspective reinforces the need for international comparative studies that can illuminate how context-specific determinants influence digital readiness and disparities across countries.

Digital health competence, defined as the knowledge, skills, and attitudes required to effectively and responsibly use digital technologies in healthcare, has become increasingly vital as healthcare professionals worldwide integrate digital solutions into their practice. These solutions range from telemedicine and clinician dashboards to AI-driven decision support. Nevertheless, professionals continue to encounter significant barriers that impede competence development (Alotaibi et al., 2025). Such obstacles include insufficient training, inadequate organisational and technical infrastructure, unclear workflows, and limited peer or managerial support (Alotaibi et al., 2025; WHO Europe, 2023). Recent research has further highlighted persistent issues such as legal and ethical uncertainties, concerns about increased workload, and disparities in access to infrastructure and training, all of which undermine digital tool adoption (WHO Europe, 2023). Although numerous digital health initiatives have been launched, empirical studies exploring the determinants of healthcare professionals' competence remain scarce, particularly in contexts beyond single institutions or countries (Jarva et al., 2024). As a result of these gaps, international comparative studies of digital health competence are urgently needed. Notably, this is the first study to apply cluster analysis to digital health competence within a broad international sample, offering novel insights into global patterns and disparities.

Over the past few years, empirical research on healthcare professionals' digital health competence has expanded significantly. A comprehensive systematic review by Longhini et al. (2022) collated 26 quantitative studies (mostly cross-sectional), revealing that most investigations assessed self-rated competences, psychological attitudes, use of technology, and theoretical knowledge, though methodological quality was often moderate to low and validated tools were rarely used. Complementing this, a recent mixed-methods systematic review (Alotaibi et al., 2025) evaluated interventions that support digital health competence and barriers that hinder its development. Using the Unified Theory of Acceptance and Use of Technology framework, they concluded that key facilitators include training, organisational support, and social influence, while complexity and poor infrastructure remain major obstacles. Both reviews collectively provide clear evidence that digital competence is unevenly distributed across professional roles, settings, and demographic profiles, and that interventions must address both individual and contextual enablers and barriers.

Given these gaps, there is an urgent need for international comparative studies on digital health competence. Such cross-national studies can reveal how diverse organisational, managerial, educational, and cultural contexts influence competence distribution and development, highlighting practices that consistently enable digital readiness across settings. Multinational consensus recommendations advocate blending top-down policy frameworks with locally tailored, bottom-up approaches to training and implementation to overcome common barriers (Galazzi et al., 2025). Comparative insights from multiple countries offer the opportunity to identify replicable strategies, pinpoint context-specific obstacles, and inform targeted policy and workforce development recommendations. Accordingly, this study, encompassing 19 countries and regions with diverse healthcare systems, cultural settings, and policy environments between 2023 and 2024, addresses a critical knowledge gap by mapping competence clusters and examining cross-national factors influencing digital readiness among healthcare professionals.

Underpinning this study is the conceptual framework developed by Jarva et al. (2023), which provides a validated basis for measuring digital health competence and its associated influencing factors across international settings. This framework operationalised digital health competence as a multifaceted construct encompassing five subdimensions: (i) usage of information and communication technologies (ICT), (ii) patient-centred digital counselling/communication, (iii) evaluation of digital tools, (iv) application of digital solutions, and (v) ethical competence in the use of digital systems. These dimensions capture critical technical abilities as well as communication, decision-making, patient interaction- and responsible digital behaviour.

In parallel, Jarva et al. (2023) developed the DigiComInf instrument, capturing three core factor domains associated with digital health competence: influence from colleagues and the work community, leadership and managerial influence, and education and orientation/training opportunities. These domains reflect the broader categorisation in our framework: organisational structures and policies, managerial practices, peer and team dynamics, as well as educational, professional and demographic characteristics.

Addressing uneven digital competence among healthcare professionals is critical to the successful adoption and integration of digital health technologies globally. To capture these variations, this study applies cluster analysis to group healthcare professionals into "competence clusters," defined as profiles of individuals who share similar levels and patterns of digital health knowledge, skills, and attitudes. By identifying these clusters and examining the factors that influence them across international contexts, the study aims to inform targeted strategies and best practices that can enhance digital readiness and capability across diverse healthcare systems and nations. Importantly, this study contributes to the expanding body of research on digital health competence and forms part of a broader research program dedicated to advancing the international assessment of competence in both research and clinical contexts. Within this program, the identification of competence clusters provides a foundation for developing scalable assessment approaches, informing evidence-based training, and supporting knowledge exchange across national and professional boundaries.

These aims align with global initiatives such as the WHO Global Strategy on Digital Health 2020–2025, which provides a roadmap for strengthening health systems through technology (WHO, 2021). Linked initiatives such as the WHO Academy seek to deliver accessible online learning to build digital health capacity worldwide. By generating comparative insights from 19 countries and regions, this study offers evidence that can support WHO-led interventions, including e-learning and policy implementation, thereby helping countries address digital competence gaps in a systematic and internationally coordinated manner.

2. Methods

2.1. Study design

This study utilised a cross-sectional international survey design, conducted across 19 countries in 2023 and 2024, to assess healthcare professionals' digital health competence and the factors influencing it. This study adhered to the STROBE (Strengthening the Reporting of Observational Studies in Epidemiology) checklist for cross-sectional studies to ensure transparency and rigour in reporting (von Elm et al., 2007).

2.2. Research aim and questions

The aim of this study was to identify distinct clusters of digital health competence among healthcare professionals across 19 countries and regions, and to examine the factors influencing the development and distribution of these competence clusters.

Research questions were: 1. What distinct clusters of digital health competence can be identified among healthcare professionals across the participating countries? 2. How do organisational, managerial, and colleague-related factors influence the digital health competence levels within each cluster? 3. What demographic, educational, and professional characteristics are associated with each competence cluster?

2.3. Participants

The data were collected from healthcare professionals across 19 countries and regions, including both primary and tertiary healthcare organisations. The inclusion criteria targeted healthcare professionals actively working in these settings, while the exclusion criteria encompassed healthcare students. A consecutive sampling strategy was employed to ensure a comprehensive and representative dataset. The required sample size was calculated using GPower software for a one-way ANOVA, assuming a medium effect size (Cohen's $f = 0.25$), an alpha level of 0.05, and a power of 0.80. This calculation indicated that a minimum of 305 participants was required to detect statistically significant differences in digital health competence and influencing factors across clusters and countries.

Overall, 6440 healthcare professionals responded to the survey. Due to differences in recruitment strategies across countries, the total number of invited participants could not be determined. After data cleaning and removal of cases with missing values, 5945 responses were retained for analysis. Records lacking all variables required for cluster analysis were deleted listwise. Recruitment strategies and the ability to calculate response rates varied considerably across countries. For instance, Finland employed a formal invitation process (23,100 invited; 817 responded), enabling a precise response rate calculation. In most other countries, however, recruitment relied on snowball sampling and distribution via professional organisations, academic networks, and digital platforms (e.g., Google Forms, REDCap, Questionnaire Star, LimeSurvey), making it impossible to determine the exact number of individuals reached or the overall response rate. Despite this limitation, these multi-channel strategies ensured wide geographical coverage and engagement of diverse professional groups across healthcare systems and contexts.

2.4. Instruments and data collection

Two instruments were utilised for data collection in this study: DigiHealthCom and DigiComInf (Jarva et al., 2022). The DigiHealthCom instrument consists of five factors and 42 items, measuring healthcare professionals' digital health competence. It included the following areas: human-centred remote counselling competence (16 items), digital solutions as part of work (9 items), information and communication technology (ICT) competence (5 items), competence in utilising and evaluating digital solutions (8 items), and ethical competence related to digital solutions (4 items). The DigiComInf instrument, comprising three factors and 15 items, assessed educational and organisational factors influencing digital health competence. It covered support from management (6 items), organisational practices for digital competence development (4 items), and colleagues' adoption and influence (5 items). Both instruments used a four-point Likert scale for scoring (1 = completely disagree, 2 = partially disagree, 3 = partially agree, 4 = completely agree). Both instruments, DigiHealthCom and DigiComInf, were back- and forward-translated into the original languages of each participating country to ensure linguistic and cultural appropriateness. The translations were further validated for content validity using the Content Validity Index (CVI) method (Polit and Beck, 2006). Additionally, both instruments were pilot-tested with a small sample of healthcare professionals to assess clarity, relevance, and usability prior to the main data collection. The results of the validation process are being reported in the work of Jarva et al. (under review), providing evidence of their reliability and validity for use in this study. Cronbach alphas varied between the factors from 0.86 to 0.97, showing the reliability of both instruments.

Data collection was conducted using a survey questionnaire comprising 10 background questions, 33 device usage questions and 57 items from the two instruments, DigiHealthCom and DigiComInf. Participating collaborating organisations in each country facilitated data collection, ensuring representative samples. Surveys were distributed electronically via email or in sealed envelopes, coordinated by a designated contact person within each organisation to support the study process. Participants received an initial invitation, followed by up to three reminders in some countries, depending on local recruitment strategies and response rates, in order to maximise participation and data completeness. In countries where paper-based questionnaires were used, reminders were not feasible.

2.5. Statistical analysis

Data analysis was conducted using IBM SPSS Statistics (Version 28). Descriptive statistics were calculated to summarise demographic characteristics, and cross-tabulations were used to evaluate relationships between variables, with statistical significance set at $p < 0.05$. K-means cluster analysis was performed to identify distinct clusters of digital health competence among participants, and one-way ANOVA was used to compare means across clusters. This analytical approach ensured a robust exploration of competence levels and their influencing factors (Everitt et al., 2011). The 5-cluster solution was deemed optimal for this study as it provided a better balance between explanatory power and alignment with the natural structure of the data. Compared to the 4-cluster solution, the 5-cluster approach consistently achieved higher eta-squared values, indicating that it explained more variance across most scores and factors. This suggests that the 5-cluster solution was better at capturing the nuances and heterogeneity present in the data. In contrast, the 4-cluster solution exhibited a notable drop in explained variance, particularly for key metrics. Furthermore, the 5-cluster solution offered a more accurate representation of the data, providing finer distinctions between groups while still maintaining sufficient simplicity for practical interpretation. Although the 4-cluster solution was simpler, it sacrificed significant explanatory power, making the 5-cluster model the preferred choice to maximise the study's analytical and interpretive depth.

Following the omnibus ANOVA, post-hoc pairwise comparisons were conducted to determine which clusters differed significantly from one another. Tukey's Honestly Significant Difference (HSD) test was applied because it controls Type I error across multiple comparisons and is appropriate when group sizes are unequal. A p-value threshold of < 0.05 (two-tailed) was used to determine statistical significance.

Effect sizes for group differences were estimated using Eta-squared (η^2), which quantifies the proportion of variance explained by the independent variable in ANOVA. Values of η^2 were interpreted following conventional benchmarks, where 0.01 indicates a small effect, 0.06 a medium effect, and 0.14 a large effect (Cohen, 1988; Richardson, 2011). This approach provided a complementary measure to the F-statistics, allowing evaluation of the practical significance of observed differences across clusters.

2.6. Ethical issues

The study was conducted in full accordance with international and national ethical standards. Each participating country obtained ethical approval or equivalent permissions as required by its respective national regulations prior to data collection. A complete list of approval numbers for all 19 participating countries is provided in Supplementary file 1. The research adhered to the principles outlined in the Declaration of Helsinki (World Medical Association, 2013), ensuring respect for participants' autonomy, privacy, and well-being. Participation in the study was entirely voluntary, and informed consent was obtained through participants' decision to complete the anonymous online questionnaire. Researchers had no direct contact with participants at any stage of the study. All data were anonymised and handled with strict confidentiality, following secure data management protocols. Furthermore, the study was conducted in compliance with the European Union's General Data Protection Regulation (GDPR; European Union, 2016), ensuring responsible processing and protection of personal data across all countries involved.

3. Results

3.1. Participants' demographics

The total sample in this study comprises 5945 healthcare professionals from 19 countries and regions, with a mean age of 41.27 years (SD = 11.81, range = 19–84) (see Table 1). Most participants were

Table 1
Full demographics summary (n = 5945).

Variable and category	Frequency (%)	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster5	p-Value
Age (*mean, SD*)	41.27 (SD = 11.81) (min-max = 19–84)	43.04 (12.27) (19–67)	43.69 (12.29) (20–69)	42.13 (11.82) (19–75)	40.26 (11.83) (19–84)	41.25 (11.37) (19–78)	<0.001
Graudation year (*mean, SD*)	2010 (SD = 11.18) (min-max = 1963–2024)	2007.16 (12.56) (1978–2024)	2007.72 (12.01) (1978–2024)	2008.64 (11.65) (1963–2024)	2010.89 (11.00) (1969–2024)	2011.43 (10.33) (1971–2024)	<0.001
Work experience (*mean, SD*)	16.48 (SD = 11.86) (min-max = 0–70)	17.54 (12.26) (0–50)	19.33 (12.56) (0–46)	17.36 (12.05) (0–70)	15.47 (11.66) (0–65)	16.49 (11.62) (0–52)	<0.001
Country							<0.001
UK	253 (4.3%)	4 (1.3%)	18 (3.4%)	33 (3.8%)	83 (3.3%)	115 (6.7%)	
Czech Republic	692 (11.6%)	24 (7.6%)	28 (5.3%)	163 (18.8%)	324 (12.8%)	153 (8.9%)	
Norway	176 (3.0%)	2 (0.6%)	13 (2.5%)	19 (2.2%)	87 (3.4%)	55 (3.2%)	
Poland	267 (4.5%)	62 (19.7%)	43 (8.2%)	66 (7.6%)	55 (2.2%)	41 (2.4%)	
Japan	284 (4.8%)	65 (20.6%)	61 (11.6%)	82 (9.5%)	63 (2.5%)	13 (0.8%)	
Singapore	137 (2.3%)	4 (1.3%)	4 (0.8%)	16 (1.8%)	92 (3.6%)	21 (1.2%)	
Lithuania	194 (3.3%)	17 (5.4%)	22 (4.2%)	22 (2.5%)	84 (3.3%)	49 (2.9%)	
Spain	229 (3.9%)	7 (2.2%)	14 (2.7%)	50 (5.8%)	103 (4.1%)	55 (3.2%)	
Austria	176 (3.0%)	2 (0.6%)	31 (5.9%)	21 (2.4%)	66 (2.6%)	56 (3.3%)	
Switzerland	273 (4.6%)	3 (1.0%)	44 (8.4%)	33 (3.8%)	105 (4.2%)	88 (5.1%)	
Germany	92 (1.5%)	2 (0.6%)	14 (2.7%)	14 (1.6%)	39 (1.5%)	23 (1.3%)	
China	402 (6.8%)	35 (11.1%)	2 (0.4%)	31 (3.6%)	156 (6.2%)	178 (10.4%)	
Finland	832 (14.0%)	27 (8.6%)	89 (17.0%)	118 (13.6%)	359 (14.2%)	239 (13.9%)	
Estonia	505 (8.5%)	8 (2.5%)	48 (9.2%)	55 (6.4%)	192 (7.6%)	202 (11.8%)	
Italy	302 (5.1%)	14 (4.4%)	13 (2.5%)	23 (2.7%)	135 (5.3%)	117 (6.8%)	
Sweden	187 (3.1%)	10 (3.2%)	41 (7.8%)	18 (2.1%)	75 (3.0%)	43 (2.5%)	
Hong Kong	517 (8.7%)	7 (2.2%)	13 (2.5%)	66 (7.6%)	309 (12.2%)	122 (7.1%)	
Philippines	120 (2.0%)	3 (1.0%)	4 (0.8%)	6 (0.7%)	54 (2.1%)	53 (3.1%)	
Taiwan	307 (5.2%)	19 (6.0%)	22 (4.2%)	30 (3.5%)	143 (5.7%)	93 (5.4%)	
Gender							0.001
Female	5020 (84.4%)	273 (86.7%)	464 (88.5%)	728 (84.1%)	2126 (84.2%)	1429 (83.3%)	
Male	852 (14.3%)	37 (11.7%)	54 (10.3%)	119 (13.7%)	365 (14.5%)	277 (16.1%)	
Other	12 (0.2%)	1 (0.3%)	1 (0.2%)	5 (0.6%)	5 (0.2%)	–	
Prefer not to answer	41 (0.7%)	4 (1.3%)	2 (0.4%)	12 (1.4%)	15 (0.6%)	8 (0.5%)	
Missing	20 (0.3%)	–	3 (0.6%)	2 (0.2%)	13 (0.5%)	2 (0.1%)	
Education							<0.001
General education	666 (11.2%)	53 (16.8%)	72 (13.8%)	130 (15.0%)	274 (10.9%)	137 (8.0%)	
Bachelor's degree	2931 (49.3%)	133 (42.2%)	256 (49.0%)	416 (48.1%)	1315 (52.2%)	811 (47.3%)	
Master's/Medical degree	1582 (26.6%)	81 (25.7%)	128 (24.5%)	217 (25.1%)	629 (25.0%)	527 (30.7%)	
Doctoral degree	613 (10.3%)	44 (4.0%)	39 (7.5%)	92 (10.6%)	252 (10.0%)	186 (10.8%)	
Other	147 (2.5%)	4 (1.3%)	27 (5.2%)	10 (1.2%)	51 (2.0%)	55 (3.2%)	
Missing	6 (0.1)	–	2 (0.4%)	1 (0.1%)	3 (0.1%)	–	
Work environment							<0.001
Hospital	4002 (67.3%)	219 (70.0%)	376 (72.0%)	585 (67.8%)	1682 (67.0%)	1140 (66.6%)	
Primary care center	697 (11.7%)	25 (8.0%)	46 (8.8%)	114 (13.2%)	296 (11.8%)	216 (12.6%)	
Home-based services	341 (5.7%)	21 (6.7%)	22 (4.2%)	46 (5.3%)	156 (6.2%)	96 (5.6%)	
Private medical center	254 (4.3%)	14 (4.5%)	13 (2.5%)	35 (4.1%)	122 (4.9%)	70 (4.1%)	
Emergency services	71 (1.2%)	5 (1.6%)	5 (1.0%)	8 (0.9%)	37 (1.5%)	16 (0.9%)	
Nursing home	245 (4.1%)	20 (6.4%)	39 (7.5%)	37 (4.3%)	93 (3.7%)	56 (3.3%)	
On-call work	52 (0.9%)	1 (0.3%)	3 (0.6%)	11 (1.3%)	22 (0.9%)	15 (0.9%)	
School/University/Research	80 (1.4%)	1 (0.3%)	2 (0.4%)	4 (0.5%)	45 (1.8%)	28 (1.6%)	
Polyclinic/Outpatient	28 (0.5%)	–	1 (0.2%)	3 (0.3%)	11 (0.4%)	13 (0.8%)	
Other	143 (2.4%)	7 (2.2%)	15 (2.9%)	19 (2.2%)	44 (1.8%)	58 (3.4%)	
Hospice/palliative care	9 (0.2%)	–	–	1 (0.1%)	4 (0.2%)	4 (0.2%)	
Missing	23 (0.4%)	2 (0.6%)	2 (0.4%)	3 (0.3%)	12 (0.5%)	4 (0.2%)	
Profession							<0.001
Nursing associate	966 (16.4%)	79 (25.2%)	69 (13.4%)	125 (14.6%)	372 (14.9%)	321 (18.9%)	
Registered nurse/public health nurse	3321 (56.5%)	188 (59.9%)	305 (59.3%)	504 (58.9%)	1450 (58.1%)	874 (51.4%)	
Midwife	178 (3.0%)	5 (1.6%)	9 (1.8%)	20 (2.3%)	80 (3.2%)	64 (3.8%)	
Physiotherapist	157 (2.7%)	4 (1.3%)	10 (1.9%)	30 (3.5%)	64 (2.6%)	49 (2.9%)	
Occupational therapist	73 (1.2%)	1 (0.3%)	5 (1.0%)	12 (1.4%)	40 (1.6%)	15 (0.9%)	
Paramedic/paramedical technician	48 (0.8%)	5 (1.6%)	4 (0.8%)	8 (0.9%)	23 (0.9%)	8 (0.5%)	
Social worker	123 (2.1%)	12 (3.8%)	10 (1.9%)	25 (2.9%)	44 (1.8%)	32 (1.9%)	
Doctor/dentist	389 (6.6%)	11 (3.5%)	21 (4.1%)	46 (5.4%)	171 (6.9%)	140 (8.2%)	
Other	624 (10.6%)	9 (2.9%)	81 (15.8%)	85 (9.9%)	252 (10.1%)	197 (11.6%)	
Missing	66 (1.1.%)	1 (0.3%)	10 (1.9%)	11 (1.3%)	28 (1.1%)	16 (0.9%)	
Amount of work							<0.001
Full-time	5138 (86.7%)	282 (89.8%)	424 (81.4%)	736 (85.2%)	2192 (87.2%)	1504 (88.0%)	
Part-time	785 (13.3%)	32 (10.2%)	97 (18.6%)	128 (14.8%)	323 (12.8%)	205 (12.0%)	
Missing	22 (0.4)	1 (0.3%)	3 (0.6%)	2 (0.2%)	9 (0.4%)	7 (0.4%)	
Working with clients							<0.001
Daily	3956 (66.8%)	215 (68.3%)	324 (61.8%)	578 (67.1%)	1719 (68.3%)	1120 (65.5%)	

(*continued on next page*)

Table 1 (*continued*)

Variable and category	Frequency (%)	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster5	p-Value
Weekly	1292 (21.8%)	77 (24.4%)	132 (25.2%)	214 (24.8%)	533 (21.2%)	336 (19.7%)	
Monthly	204 (3.4%)	13 (4.1%)	13 (2.5%)	32 (3.7%)	80 (3.2%)	66 (3.9%)	
Less frequently	137 (2.3%)	6 (1.9%)	7 (1.3%)	7 (0.8%)	57 (2.3%)	60 (3.5%)	
I do not currently work with clients/patients	336 (5.7%)	4 (1.3%)	48 (9.2%)	31 (3.6%)	126 (5.0%)	127 (7.4%)	
Missing	20 (0.3)	1 (0.3%)	3 (0.6%)	4 (0.5%)	9 (0.4%)	7 (0.4%)	

female (84.4%), with 49.3% holding bachelor's degrees, 26.6% having master's or medical degrees, and 10.3% holding doctoral degrees. The majority worked full-time (86.7%) in hospitals (67.3%), while others were employed in primary care centres (11.7%), home-based services (5.7%), and nursing homes (4.1%). The most common professions were registered nurses and public health nurses (56.5%), followed by nursing associates (16.4%), with smaller representations from medical doctors/dentists (6.6%), social workers (2.1%), and other healthcare professional roles. While a small proportion of respondents (2%) were social workers, given the study's primary scope and the predominance of healthcare professionals in the sample, the analyses are reported with a focus on healthcare professionals.

3.2. Distinct clusters of digital health competence and background factors

The analysis of the DigiHealthCom and DigiComInf variables reveals highly significant differences across five clusters, with all tested factors yielding p-values below 0.001 (see Tables 2–3, Figs. 1–3). Fig. 1 provides an integrated visual summary of the five digital health competence clusters, illustrating both their proportional distribution and the corresponding mean scores of digital competence and influential organisational factors. The F-values were notably high, indicating substantial group-level differences, particularly for the DigiHealthCom total score ($F = 8323.045$) and its subscale (F1), as well as Counselling ($F = 6788.816$). Effect sizes, measured via Eta-squared (η^2), were substantial in most cases, with the largest observed in the DigiHealthCom total ($\eta^2 = 0.86$) and F1: Counselling ($\eta^2 = 0.829$), suggesting that a significant proportion of variance is attributable to the tested factors.

In contrast, DigiComInf variables, while still statistically significant, show smaller effect sizes (η^2 ranging from 0.113 to 0.166), indicating comparatively smaller between–group differences (see Supplementary file 2). Post-hoc comparisons using the Bonferroni correction confirmed that mean differences between clusters were statistically significant in nearly all pairwise comparisons, reinforcing the robustness of findings against Type I error. Exceptions to this pattern included the following non-significant comparisons. Cluster 2 and Cluster 4 for DigiHealthCom (F2) Digital solutions score and (F3) ICT, Cluster 2 and Cluster 3 for (F4) utilising and evaluating score, as well as between Cluster 2 and Cluster 3 for (F5) Ethics Score. Additionally, Cluster 2 and Cluster 4 did not differ significantly for DigiComInf (F3) Colleagues' score.

3.2.1. Cluster 1: beginners

This group, which constituted 5.3% of the sample, exhibited the lowest digital competence scores across all measured dimensions (see Table 2, Fig. 2). This cluster had the lowest competence levels across all dimensions, with particularly low scores in (F1) Counselling (1.5) and (F4) Utilising and evaluating (1.56). Their performance was consistently below that of all other clusters, reflecting significant challenges in adopting and utilising digital health tools. Cluster 1 perceived the lowest influence of all factors on their competence, with particularly low perceptions for (F2) Organisation (1.8) (see Fig. 3).

Participants in this cluster often struggled with basic digital tools or demonstrated reluctance to adopt them. The cluster included a notable proportion of individuals from Japan (20.6%), Poland (19.7%), and China (11.1%), while representation from countries such as Norway, Austria, and Germany was minimal (each at 0.6%). Members of this cluster tended to be older, with a mean age of 43 years, and were more likely to possess general education qualifications (16.8%) compared to other clusters. Nursing associates formed the largest group (25.2%), with significant representation of registered nurses and public health nurses (59.9%) alongside smaller proportions of social workers (3.8%), doctors/dentists (3.5%), and paramedics (1.6%), reflecting a focus on foundational and support healthcare roles.

This group also stood out with earlier average graduation years (2007), suggesting that their professional training may have predated the widespread integration of digital tools in healthcare education. This timing could have partially explained their lower digital competence. Despite having moderate work experience (17.54 years for Cluster 1, closely aligned with 17.36 years for Cluster 3), participants in this cluster reported limited daily interaction with digital tools. 6.6% indicated at work no use of computers, 23.6% smartphones, 54.4% tablets, 69.4% wearables and 80% no robotics (see Supplementary file 3).

Professionally, the majority worked in settings such as hospitals (70.0%), primary care centres (8.0%), home-based services (6.7%), and nursing homes (6.4%). Additionally, this cluster had a higher proportion of women (86.7%) and individuals with general education qualifications (16.8%), further reflecting demographic and educational characteristics that may have contributed to their lower digital competence.

3.2.2. Cluster 2: developing professionals

This cluster, which comprised 8.8% of the sample, represented professionals with moderate digital competence who were gradually adopting and integrating digital health tools into their practices. Cluster 2 exhibited a unique pattern, characterised by very low competence in Counselling (F1) (1.42) but higher scores in ICT (F3) (3.58). This indicated uneven competence, with strengths in technical areas but challenges in applying digital tools in counselling or ethical contexts (F5, 2.27). Cluster 2 perceived moderate levels of influence from the factors, with (F1) Management (2.69) and (F3) Colleagues (2.87) seen as slightly more impactful. However, their relatively low perception of (F2) Organisation (2.41) indicated that organisational structures were not seen as strongly supportive of their competence development.

Participants were predominantly from Finland (17.0%) and Japan (11.6%), with fewer representatives from countries like China (0.4%), Singapore (0.8%), and the Philippines (0.8%). Cluster 2 shared demographic similarities with Cluster 1, including an older age profile, with a mean age of 43.69 years, the highest among all clusters. Educationally, participants in this cluster were more likely to hold bachelor's degrees (49.0%) compared to Cluster 1, reflecting a slightly higher level of formal education. With the longest mean work experience of 19.33 years, these experienced professionals may have relied more heavily on established, traditional practices, which could have influenced their pace of adopting digital tools. Registered nurses and public health nurses dominated (59.3%), followed by nursing associates (13.4%), social workers and physiotherapists (1.9%), and doctors/dentists (4.1%), with minimal representation from occupational therapists (1.0%), indicating a mix of clinical and allied health professions.

Digital tool usage was moderate, with no use of wearables (78.9%) or robotics (88.1%), indicating a slower uptake of emerging technologies. Professionally, most participants worked in hospital settings (72.0%), yet their exposure to advanced digital tools appeared constrained.

Cluster 2 also had a high proportion of women (88.5%), slightly

Table 2
Descriptive statistics of five clusters.

Variable	Total sample size	Total 100% Mean (SD)	Cluster 1 5.3% Mean (SD. min-max)	Cluster 2 8.8% Mean (SD. min-max)	Cluster 3 14.6% Mean (SD. min-max)	Cluster 4 42.5% Mean (SD. min-max)	Cluster 5 28.9% Mean (SD. min-max)
DigiHealthCom total score	5447	2.88 (0.47)	1.6 (0.32) (1.0–2.12)	2.28 (0.25) (1.64–2.95)	2.51 (0.19) (1.93–2.95)	3.0 (0.14) (2.64–3.74)	3.3 (0.15) (2.55–4.0)
DigiHealthCom F1: Counselling	5613	2.89 (0.76)	1.5 (0.46) (1.0–2.88)	1.42 (0.4) (1.0–2.25)	2.55 (0.37) (1.75–4.0)	2.97 (0.26) (2.06–3.81)	3.64 (0.29) (2.94–4.0)
DigiHealthCom F2: Digital solutions	5833	3.17 (0.67)	1.64 (0.54) (1.0–3.44)	3.17 (0.53) (1.89–4.0)	2.48 (0.46) (1.0–3.78)	3.2 (0.38) (1.67–4.0)	3.74 (0.32) (2.11–4.0)
DigiHealthCom F3: ICT	5893	3.47 (0.65)	1.93 (0.79) (1.0–4.0)	3.58 (0.44) (1.4–4.0)	3.02 (0.71) (1.0–4.0)	3.55 (0.41) (1.0–4.0)	3.84 (0.33) (1.0–4.0)
DigiHealthCom F4: Utilising/evaluate	5777	2.39 (0.46)	1.56 (0.51) (1.0–3.0)	2.19 (0.47) (1.0–3.25)	2.21 (0.43) (1.0–3.0)	2.66 (0.32) (1.13–4.0)	2.31 (0.34) (1.0–4.0)
DigiHealthCom F5: Ethical	5798	2.38 (0.49)	1.64 (0.57) (1.0–3.0)	2.27 (0.51) (1.0–3.75)	2.36 (0.46) (1.0–3.25)	2.61 (0.41) (1.0–4.0)	2.22 (0.37) (1.0–4.0)
DigiComInf total score	5652	2.77 (0.67)	1.97 (0.72) (1.0–4.0)	2.66 (0.65) (1.0–4.0)	2.45 (0.58) (1.0–4.0)	2.8 (0.55) (1.0–4.0)	3.06 (0.68) (1.0–4.0)
DigiComInf F1: Management	5743	2.83 (0.81)	2.02 (0.85) (1.0–4.0)	2.69 (0.81) (1.0–4.0)	2.49 (0.75) (1.0–4.0)	2.87 (0.7) (1.0–4.0)	3.13 (0.81) (1.0–4.0)
DigiComInf F2: Organisation	5758	2.58 (0.83)	1.8 (0.76) (1.0–4.0)	2.41 (0.82) (1.0–4.0)	2.25 (0.75) (1.0–4.0)	2.62 (0.71) (1.0–4.0)	2.88 (0.87) (1.0–4.0)
DigiComInf F3: Colleagues	5755	2.86 (0.68)	2.06 (0.78) (1.0–4.0)	2.84 (0.64) (1.0–4.0)	2.55 (0.59) (1.0–4.0)	2.87 (0.57) (1.0–4.0)	3.13 (0.69) (1.0–4.0)

surpassing other clusters. These demographic and professional characteristics suggested a group that, while competent, was still transitioning toward full utilisation of digital health innovations.

3.2.3. *Cluster 3: emerging users*

Cluster 3, which represented 14.6% of participants, consisted of professionals with balanced digital competence and moderate engagement with digital health tools. This cluster exhibited moderate competence levels across dimensions, with the highest scores in (F3) ICT (3.02) and lower performance in (F2) Digital Solutions (2.48) and (F5) Ethical Issues (2.36). Their competence was balanced but not as advanced as that of Clusters 4 and 5. Cluster 3 exhibited balanced but relatively low perceptions of influencing factors, particularly for (F2) Organisation (2.25) and (F1) Management (2.49). This group perceived organisational and managerial support as less influential in enhancing their competence, though they saw colleagues as a somewhat stronger influence (F3) Colleagues, 2.55.

This cluster included a significant proportion of participants from the Czech Republic (18.8%) and Finland (13.6%), with fewer representatives from countries such as the Philippines (0.7%) and Germany (1.6%). Educational attainment was variable, but bachelor's degrees were prevalent (48.1%), reflecting a relatively strong academic foundation. Registered nurses and public health nurses were the majority (58.9%), while a diverse mix included nursing associates (14.6%), social workers (2.9%), doctors/dentists (5.4%), physiotherapists (3.5%), and paramedics (0.9%), highlighting balanced representation of various healthcare roles. The group's moderately recent average graduation year (2008) suggested that many participants had some exposure to digital training during their education.

Daily use of digital tools varied, with no engagement with computers (1.7%) and moderate usage of smartphones (19.9%) and tablets (56.6%). However, interaction with advanced technologies remained limited, as 87.2% reported no use of robotics.

Professionally, participants were most likely to work in hospitals (67.8%), primary care centres (13.2%), or nursing homes (4.3%), indicating diverse healthcare settings that may have influenced their exposure to digital tools. Members of this cluster were also actively involved in self-education and digital competence-building initiatives, highlighting a willingness to improve their digital skills. Women made up 84.1% of this cluster, reflecting the broader gender distribution within the healthcare workforce.

3.2.4. *Cluster 4: proficient practitioners*

As the largest group, comprising 42.5% of participants, Cluster 4 represented professionals with average digital competence across all measured dimensions. Cluster 4 maintained average to above-average competence, performing consistently well across dimensions. Their most substantial area was (F3) ICT (3.55) and (F2) Digital solutions (3.20), with the weakest areas shown in (F6) Ethical issues (2.61) and (F4) Utilising and evaluation (2.66). Cluster 4 perceived above-average levels of influence across all factors, with (F3) Colleagues (2.87) and (F1) Management (2.87) perceived as the most significant influences. (F2) Organisational support (2.62) was also viewed positively, suggesting that this group felt moderately supported by their work environments and colleagues.

This cluster was geographically diverse, with notable representation from Finland (14.2%), the Czech Republic (12.8%), and Hong Kong (12.2%), and smaller contributions from countries like Germany (1.5%) and the Philippines (2.1%). Cluster 4 participants had the youngest mean age (40 years), with a broad age range spanning 19 to 84 years and relatively consistent age diversity. This cluster was predominantly composed of registered nurses and public health nurses (58.1%) and nursing associates (14.9%), alongside midwives (3.2%), doctors/dentists (6.9%), and social workers (1.8%), reflecting professionals from both clinical and community-based roles. Their average graduation year (2010) reflected a more recent educational background, closely aligned

Table 3
One-way ANOVA between five clusters.

Variable	Between SS	Within SS	df	F-value	p-Value	Eta-squared
DigiHealthCom total score	1035.819	169.317	4. 5442	8323.045	<0.001	0.86
DigiHealthCom F1: Counselling	2656.161	548.54	4. 5608	6788.816	<0.001	0.829
DigiHealthCom F2: Digital solutions	1659.562	942.243	4. 5828	2566.198	<0.001	0.638
DigiHealthCom F3: ICT	1157.796	1340.322	4. 5888	1271.542	<0.001	0.463
DigiHealthCom F4: Utilising/evaluat	445.77	786.102	4. 5772	818.272	<0.001	0.362
DigiHealthCom F5: Ethical	350.135	1059.322	4. 5793	478.686	<0.001	0.248
DigiComInf total score	424.616	2132.756	4. 5647	281.069	<0.001	0.166
DigiComInf F1: Management	454.912	3291.438	4. 5738	198.263	<0.001	0.121
DigiComInf F2: Organisation	447.153	3504.021	4. 5753	183.537	<0.001	0.113
DigiComInf F3: Colleagues	396.218	2278.129	4. 5750	250.014	<0.001	0.148

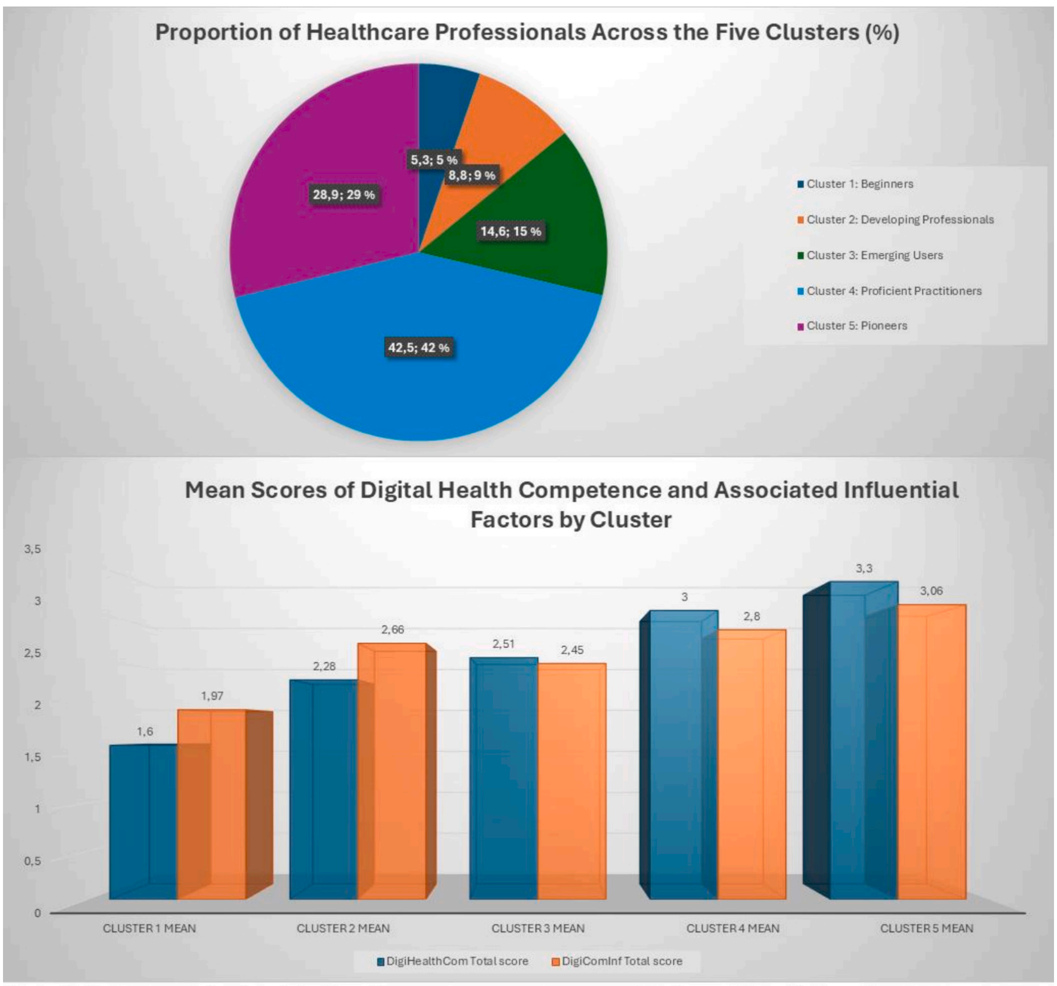

Fig. 1. Overview of the five digital health competence clusters and their associated influential factors.

with Cluster 5 (2011). This timing suggested greater exposure to digital tools during their training, which likely contributed to their digital competence. With the lowest mean work experience (15.47 years), Cluster 4, aligned with its younger age profile, indicates that participants were earlier in their careers and may have demonstrated greater adaptability to digital technologies due to fewer ingrained professional habits.

Daily use of digital tools was common, with low rates of not using computers at work (1.4%) and smartphone (16.5%) usage, alongside moderate engagement with digital services (48.8% reported usage). Most participants worked in standard healthcare settings, primarily hospitals (67.0%) and primary care centres (11.8%). Women constituted the majority (84.2%), and bachelor's degrees were prevalent (52.2%), reflecting the typical composition of the healthcare workforce.

3.2.5. *Cluster 5: pioneers*

Cluster 5, which represented 28.9% of participants, demonstrated the highest digital competence scores across all dimensions. Cluster 5 exhibited the highest competence across all dimensions, particularly excelling in (F3) ICT (3.84), (F2) Digital solutions (3.74), and (F1) Counselling (3.64). Their overall scores indicated advanced digital health competence, with consistent strength in both technical and applied dimensions. Cluster 5 perceived the strongest influence of all factors on their competence, with (F1) Management (3.13) and (F3) Colleagues (3.13) seen as the most impactful, and (F2) Organisation (2.88) also rated highly. This indicated that participants in this cluster

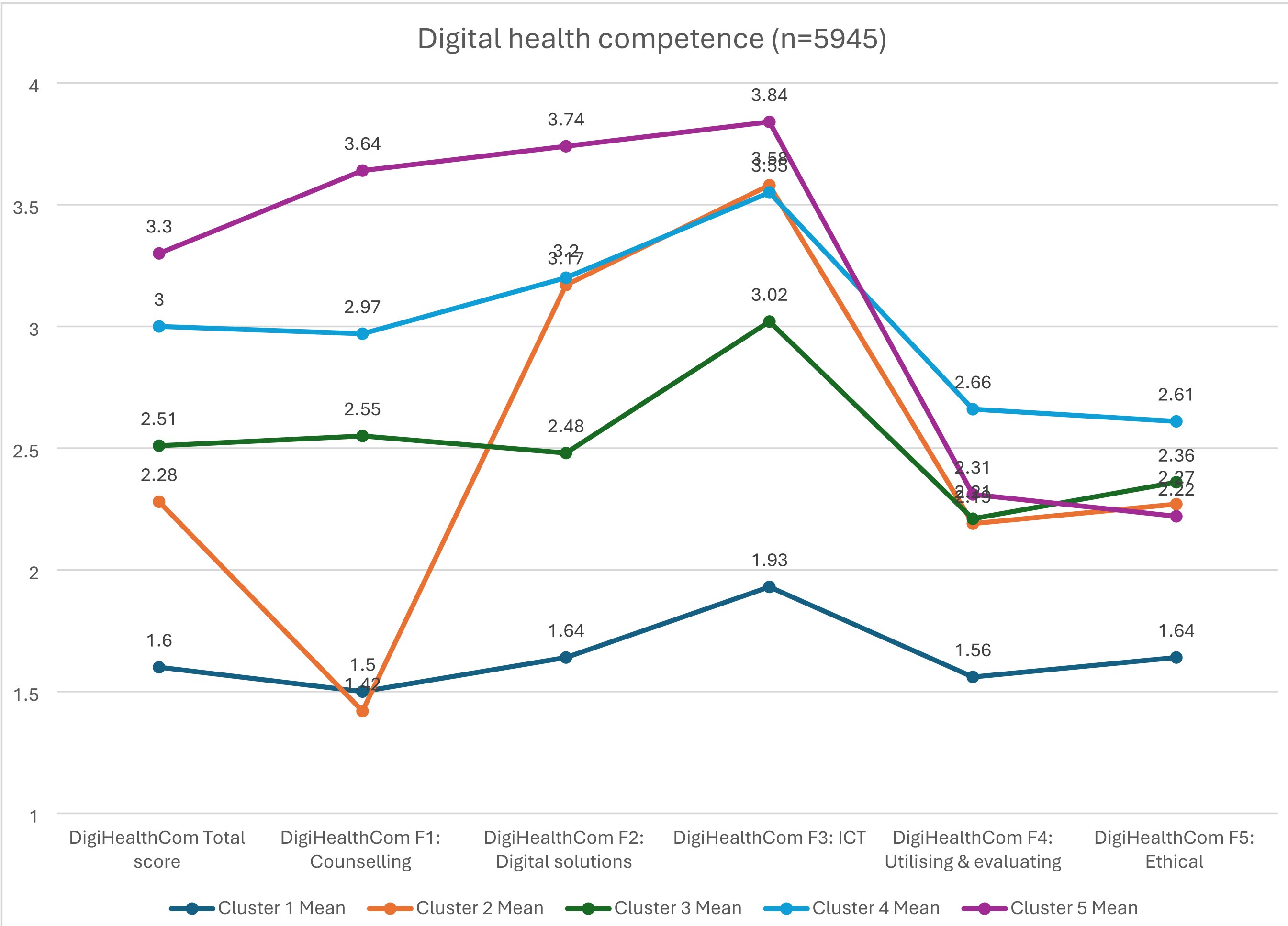

Fig. 2. Cluster presentation of healthcare professionals' digital health competence.

felt strongly supported by their management, colleagues, and organisational structures in fostering their competence.

This group was geographically diverse, with significant representation from Finland (13.9%), Estonia (11.8%), and China (10.4%). In contrast, countries like Japan (0.8%), Singapore (1.2%), and Germany (1.3%) had fewer participants in this cluster. Educationally, Cluster 5 participants stood out, with 30.7% holding master's degrees, reflecting higher levels of formal education compared to other clusters. While registered nurses and public health nurses remained the largest group (51.4%), this cluster included the highest proportion of doctors/dentists (8.2%), as well as nursing associates (18.9%), midwives (3.8%), and social workers (1.9%), showcasing a concentration of advanced and specialised healthcare professionals.

They also reported extensive daily use of digital tools. Engagement with advanced technologies was particularly high when compared to other clusters, indicating strong adoption of innovative healthcare tools.

Professionally, most participants worked in hospitals (66.6%), with smaller proportions in nursing homes (3.3%). The group had the highest proportion of male participants (16.1%). These characteristics underscore the advanced digital proficiency of this cluster, driven by their educational background and frequent interaction with cutting-edge technologies in their work environments.

4. Discussion

This study identified five distinct clusters of digital health competence among healthcare professionals across 19 countries and regions, reflecting varying levels of digital competence and factors associated with it. Cluster 1 (Beginners) exhibited limited digital engagement, highlighting a critical need for foundational training and targeted interventions, particularly in primary care and nursing home settings. Cluster 2 (Developing Professionals) showed moderate but emerging digital competence, indicating significant potential for competence growth with structured support. Cluster 3 (Emerging Users) represented individuals with moderate proficiency who were actively improving their digital skills through self-directed learning, requiring structured mentorship for full integration. Cluster 4 (Proficient Practitioners) demonstrated solid digital health competence, effectively incorporating digital tools into their daily practice, serving as key contributors to organisational digital transformation. Cluster 5 (Pioneers) encompassed digitally proficient leaders, characterised by their role as early adopters and innovators, significantly driving digital health integration.

Key influencing factors identified included organisational structures, managerial support, and peer collaboration, strongly correlating with competence levels across clusters. Notably, management support emerged as a pivotal driver of digital competence, particularly in higher-performing clusters. Conversely, lower competence clusters reported insufficient organisational, managerial, and peer support, highlighting systemic barriers to competence development. This suggests a clear pathway for targeted interventions, emphasising leadership engagement, organisational resources, and collaborative learning environments to enhance digital competence across diverse professional groups.

The identified clusters offer fresh clarity to the landscape of healthcare professionals' digital health competence, paralleling the nuanced

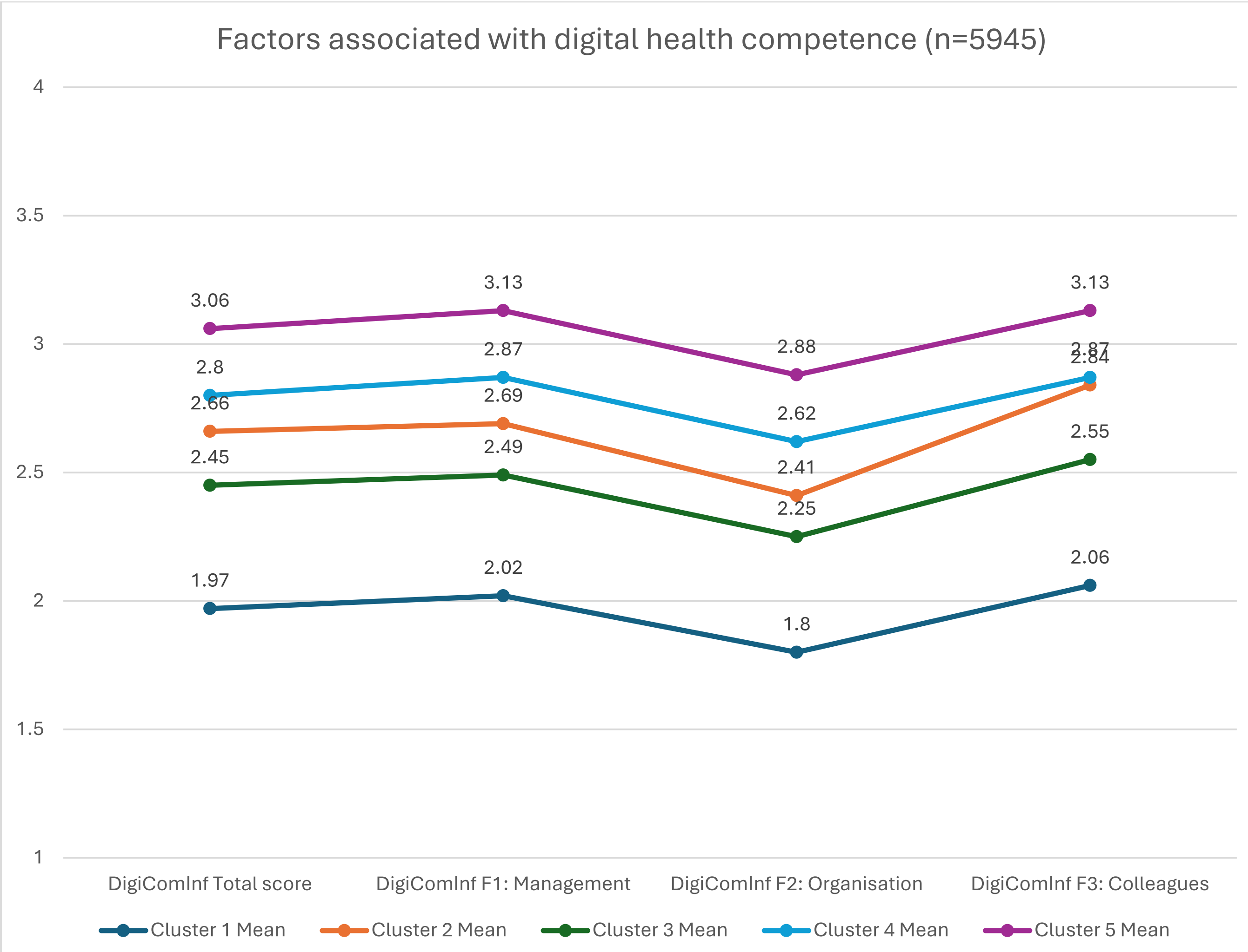

Fig. 3. Cluster presentation of factors associated with healthcare professionals' digital health competence.

profiles found in multiple contemporary studies. For example, a large-scale cross-sectional survey of 643 professionals in Finland emerged with seven distinct competence profiles, categorised into motivated digital experts, burdened digital users and frustrated survivors (Ylönen et al., 2025). Similarly, in Ethiopian public health centres, a 2020 survey using the EU's digital competency framework found that over half of healthcare providers exhibited basic or low-level digital competence, particularly in problem-solving, safety and communication, highlighting significant foundational gaps often correlated with low education and experience (Shiferaw et al., 2020). These findings resonate with Cluster 1 (Beginners) in this study, a group characterised by minimal engagement and limitation in technical, communicative or evaluative digital capacities. In a Swiss mental health hospital study (Golz et al., 2021), digital competence was negatively associated with technostress: professionals with higher perceived competence reported lower stress, even though some overestimated their abilities. Older age and certain roles also predicted stress levels. This mirrors our observation that Clusters 2–3 may possess moderate or self-rated skills but remain vulnerable to misestimations and require structured guidance to reach proficiency. In the UK subsample of this study, greater professional experience was associated with higher levels of digital competence, particularly regarding the ethical use of digital solutions (Erfani et al., 2025).

In this vein, it is important to differentiate the specific domain of digital competence among healthcare professionals in order to design tailored mentoring opportunities and strategies. For example, while experienced healthcare professionals can support novice healthcare professionals in the ethical aspects of digital solutions, the novices can mentor more experienced colleagues regarding the ICT aspects (Erfani et al., 2025). This would suggest the implementation of reverse-mentoring strategies, where younger generations can develop older generations' digital competences (Hammarén et al., 2024).

A qualitative study from Finland and Sweden (2022) spotlighted how competence development is shaped by managerial role-modelling, continuous education using digital and social media tools, and strong peer networks (Jarva et al., 2022). These social and educational enablers map directly onto our conceptual framework factors (Jarva et al., 2023), particularly those influencing Clusters 3, 4 and 5, where mentorship, organisational culture, and leadership support reinforce profile progression. In this study, findings from the UK subsample further indicated that healthcare professionals in managerial positions demonstrated more advanced organisational digital competences and played a key role in promoting environments conducive to digital competence development (Erfani et al., 2025). Collectively, these studies illustrate that digital competence varies across educational levels, settings, and professional experiences, just as our clusters do. The consistency in patterns across settings supports our model's assertion that distinct competence clusters emerge based on combinations of technical, communication, evaluative, ethical and adaptability dimensions. This reinforces the importance of designing interventions and policies tailored to these differentiated profiles for effective digital transformation in healthcare.

This study emphasises that healthcare professionals' digital health competence is deeply embedded in broader organisational environments. For instance, a multinational method consensus study led by Galazzi et al. (2025) validated recommendations urging health organisations to deliver both technical and organisational support, especially training, infrastructure access, and system usability enhancements, to effectively foster competence development. Conversely, a systematic review of barriers to digital competence highlighted that lack of training, complex systems, and insufficient infrastructure are primary obstacles, reinforcing why beginners and developing clusters underperform in lower-resourced environments (Alotaibi et al., 2025).

Leadership practices also emerged as pivotal. Steenkamp et al. (2025) found that healthcare leaders generally exhibit positive motivation and attitudes toward digital transformation; however, their readiness to effectively drive digital change is often limited by insufficient organisational support, inadequate leadership capacity, and a lack of a supportive organisational culture. Complementing this, a qualitative study in Finnish health centres revealed that misalignment between managers' and professionals' views on digitalisation can undermine competence development unless dialogue and shared understanding are maintained (Kaihlanen et al., 2023). Organisational transformational leadership theory (Bass and Riggio, 2006) supports that effective leadership entails visible commitment, role modelling, and participatory decision-making, which, in our study, relating to digital health, can be observed in high-performing clusters.

Peer influence likewise plays a crucial enabling role. A concept analysis on leadership in the context of digital health services conducted by Laukka et al. (2022) demonstrated that peer networks, mentoring, and collaborative learning greatly enhanced digital competence progression, which is particularly important for the interpretation of our study for clusters transitioning from moderate to high levels. This aligns with social learning theory and research on competence sharing, which stresses the effectiveness of peer-supported environments in lowering barriers and reinforcing positive digital norms (Hammarén et al., 2024; Longhini et al., 2022).

Healthcare professionals' digital health competence was significantly shaped by demographic and professional attributes such as education level, role, and experience. A scoping review by Mainz et al. (2024) further emphasised that digital competence embodies multiple domains, technical, methodological, social, and personal, and that existing measurement tools often overemphasise technical skills at the expense of adaptive and reflective capacity. This supports our view that younger clusters with postgraduate qualifications and digital exposure tend also to exhibit stronger adaptability, traits central to the Digital Adaptability Competency framework described by Bleijenbergh et al. (2023) and consistent with the model tested by Erfani et al. (2025) in which higher educational levels are associated with higher digital competence.

To address these demographic disparities, workforce training strategies should be differentiated and context-specific. For those in Clusters 1 and 2, interventions could begin with foundational digital literacy modules, accessible through flexible formats (e.g. online short courses or workshops) and tailored to lower-education or non-hospital settings, aligning with approaches recommended in low-resource contexts like Ethiopia (Shiferaw et al., 2020), but also with the findings from the UK, where it was demonstrated that digital competences are lower among the healthcare professionals with undergraduate education and working in non-hospital settings (Erfani et al., 2025). At the European level, initiatives such as the European approach to micro-credentials and the European Qualifications Framework (EQF) provide mechanisms for aligning, recognising, and comparing qualifications across countries (European Commission, 2008). Micro-credentials offer flexible, modular pathways for upskilling, while the EQF creates a shared reference point that enhances transparency and cross-country comparability of knowledge, skills, and competences. Integrating digital health competence into these frameworks could facilitate the development of scalable, internationally aligned training programs. Expanding such frameworks beyond the EU could further enable reciprocity, supporting the creation of targeted educational programs that respond to specific workforce needs while maintaining international coherence and transferability.

Healthcare professionals with undergraduate education often lack sufficient digital health competence, possibly because their faculty, while generally at an intermediate level, integrate digital technologies inconsistently, with competence influenced by age, prior digital teaching experience, and the work environment (Ersoy et al., 2024). For Clusters 3 and 4, structured upskilling programmes featuring mentorship, case-based digital simulations, and team-based learning can reinforce transition to higher competence levels. Importantly, Cluster 5 professionals, digital pioneers, often with postgraduate training, are well-positioned to serve as peer mentors or champions, helping co-design digital curriculum, support inter-professional learning, and spread advanced digital practices across the organisation. Tailoring training by education level, role, experience, and digital experience is essential for reducing generational divides and elevating organisational digital readiness. Advanced Extended Reality and Artificial Intelligence teaching methods offer promising avenues for developing complex, multidimensional pedagogical frameworks (Mikkonen et al., 2024, 2025). These innovative approaches enable realistic, immersive, and personalised learning experiences, which can effectively be integrated into organisational upskilling and continuous education structures. By leveraging extended reality (XR) and artificial intelligence (AI), organisations can deliver high-quality training efficiently and sustainably, requiring fewer resources compared to traditional educational methods.

4.1. Practical implications and recommendations

The findings of this study offer actionable insights for targeted strategies in digital health education and workforce development. By identifying distinct competence clusters, organisations and policymakers can tailor interventions that reflect the specific needs of healthcare professionals at different proficiency levels. This includes integrating structured digital skill-building pathways into competence frameworks and continuing professional development programmes. Furthermore, aligning organisational training with real-world digital demands, through modular, peer-supported, and role-specific initiatives, can accelerate digital readiness across the workforce (Konttila et al., 2019).

4.2. Implications for nursing practice and education

For the nursing profession, the identified digital competence clusters have several discipline-specific implications. Nurses, who represent the largest segment of the global healthcare workforce, play a central role in patient monitoring, clinical decision-making, coordination of care, and patient education, all of which increasingly rely on digital health tools. The lower-competence clusters (Clusters 1–2), where many nurses in primary care, community care, and long-term care settings are represented, underline the persistent gap in access to structured digital training opportunities. Strengthening foundational competence among nurses is essential, as digital documentation systems, remote monitoring technologies, and telehealth platforms are now core components of everyday nursing practice.

Simulation-based education provides a particularly powerful strategy for building these competences (Ropponen et al., 2025). Low-fidelity simulations, such as task trainers or basic digital exercises, can support nurses in developing foundational digital literacy and confidence, especially for those in the Beginner or Developing clusters. Meanwhile, high-fidelity simulations incorporating advanced digital tools, including immersive virtual reality (VR) or augmented reality (AR), can prepare nurses in more advanced clusters to apply digital skills in complex clinical scenarios (Mikkonen et al., 2025). Integrating VR into clinical simulation not only enhances realism but also enables safe exposure to rare or high-risk situations, supporting the transition from moderate to advanced competence levels.

The cluster findings also highlight the value of interprofessional and peer-supported simulation environments. Nurses in Clusters 3–5 can benefit from mentorship structures where digitally proficient nurses or nurse educators act as champions, facilitating hands-on sessions, scenario design, and reflective debriefing focused on digital workflow integration. The insights from this study support incorporating digital health competence, including simulation-based digital skills, into nursing curricula, continuing professional development, and clinical onboarding programmes. Such alignment strengthens nurses' readiness for technology-enhanced care and contributes directly to organisational digital maturity.

4.3. Directions for future research

Further investigation is warranted to explore the longitudinal development of digital competence and the sustained impact of targeted interventions. Future studies should include interventional research that evaluates the effectiveness of specific training models, such as mentorship programmes, AI-enhanced simulations, or XR-based learning, across different organisational and cultural settings. Cross-country comparative research could also shed light on how contextual variables shape competence development, digital innovation adoption, and the capacity to address critical challenges such as cybersecurity risks and ethical issues in healthcare.

4.4. Limitations and strengths

This study has several limitations that should be acknowledged. First, although a power analysis determined that a minimum of 305 participants per country was needed to ensure adequate statistical power, nearly half of the participating countries did not meet this threshold. Nonetheless, the observed effect sizes in the cluster and group comparison analyses were moderate to strong, supporting the overall robustness of the findings. Second, the economic disparities among countries may influence the availability and maturity of digital health infrastructure, potentially affecting digital competence. While this contextual factor is theoretically relevant, it was not clearly reflected in the current data, possibly due to the nature of the self-assessment measures or cross-sectional design. The generalisability of the findings is limited by the geographical scope of the data, as participants were not recruited from North or South America, Africa, or Australia; however, the study provides strong representation from Europe and Asia, offering valuable insights into digital health competence across these regions. Further limitation concerns the reliance on self-reported measures of digital health competence. Although the DigiHealthCom and DigiComInf instruments were validated and demonstrated high internal consistency, self-assessment may not fully capture actual competence levels. Respondents may overestimate or underestimate their abilities due to social desirability, lack of objective benchmarks, or differing cultural interpretations of competence items. Future research should complement self-reported data with objective assessments of digital competence (e.g., performance-based tasks, simulations, or supervisor evaluations) to provide a more accurate and comprehensive picture of healthcare professionals' digital competence.

It is also important to consider that, in some cases, the data collection strategy, although methodologically rigorous and harmonised, might have led to digital exclusion, particularly when an online survey was the sole method used. In this context, potential participants with limited access to digital tools or those less inclined to complete an online survey may have been underrepresented.

Despite these limitations, the study also presents several notable strengths. The data collection process followed a consistent and structured protocol across countries, including the use of shared instruments, agreed demographic categories, and predefined procedures. Regular coordination meetings and strong international collaboration ensured high data integrity and methodological alignment. Furthermore, each participating country committed to analysing and disseminating their national data independently, with Finland (Jarva et al., 2024), the United Kingdom (Erfani et al., 2025), the Czech Republic (Mandysova et al., 2025), and China (Gao et al., 2025a, 2025b) having already published country-specific findings, adding further depth and validation to the overall research effort.

A key limitation of this study concerns the lack of comprehensive data on invitation numbers and response rates across participating countries. While formal invitation records were available in Finland, enabling calculation of a response rate, in most countries, recruitment relied on snowball sampling, professional organisations, and digital platforms. As a result, the total number of healthcare professionals invited could not be reliably estimated, and response rates could not be consistently calculated. Even in Finland—where the highest response rate was achieved—the participation level remained low, and in several other countries it was extremely low. This constitutes a significant limitation and requires that the results be interpreted with considerable caution. This restricts the ability to assess potential non-response bias and limits comparability across countries. Nevertheless, the multichannel recruitment strategies employed ensured broad geographical coverage and inclusion of diverse professional groups, which strengthens the representativeness of the findings despite these limitations.

5. Conclusions

This study advances our understanding of the diverse digital competence profiles among healthcare professionals and the organisational and individual factors that shape them. These insights are crucial for building scalable, equitable, and effective digital capacity within healthcare systems globally, laying a foundation for workforce strategies that are both responsive and future-oriented.

CRediT authorship contribution statement

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ijnurstu.2026.105348.

Data availability

All data generated and analysed in this study are presented in full within this publication. No additional data are available for sharing.

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